

Prediction and Analysis of Large-Scale Stock Market Risk Correlation Structure

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Introduction: The prediction of the high-dimensional dependence structure among global stock markets is an advanced topic in financial risk management. However, the complex structure characterized by high dimensionality, nonlinearity, and asymmetry, presents significant challenges for conventional financial models to systematically and efficiently predict and analyze large-scale cross-market correlation structures.

We accelerate the correlation structure decomposition across 36 countries by hundreds of threads in parallel. And then we study the correlation structure of large-scale stock markets using deep learning algorithms to overcome the uncomputable limitations, such as RNN, LSTM, GRU, and improved versions of these three algorithms, including Average Weighted Ensemble Algorithm(AWEA), Encoder-Decoder Algorithm with Attention(EDAA), and Random Forest Ensemble Algorithm(RFEA).

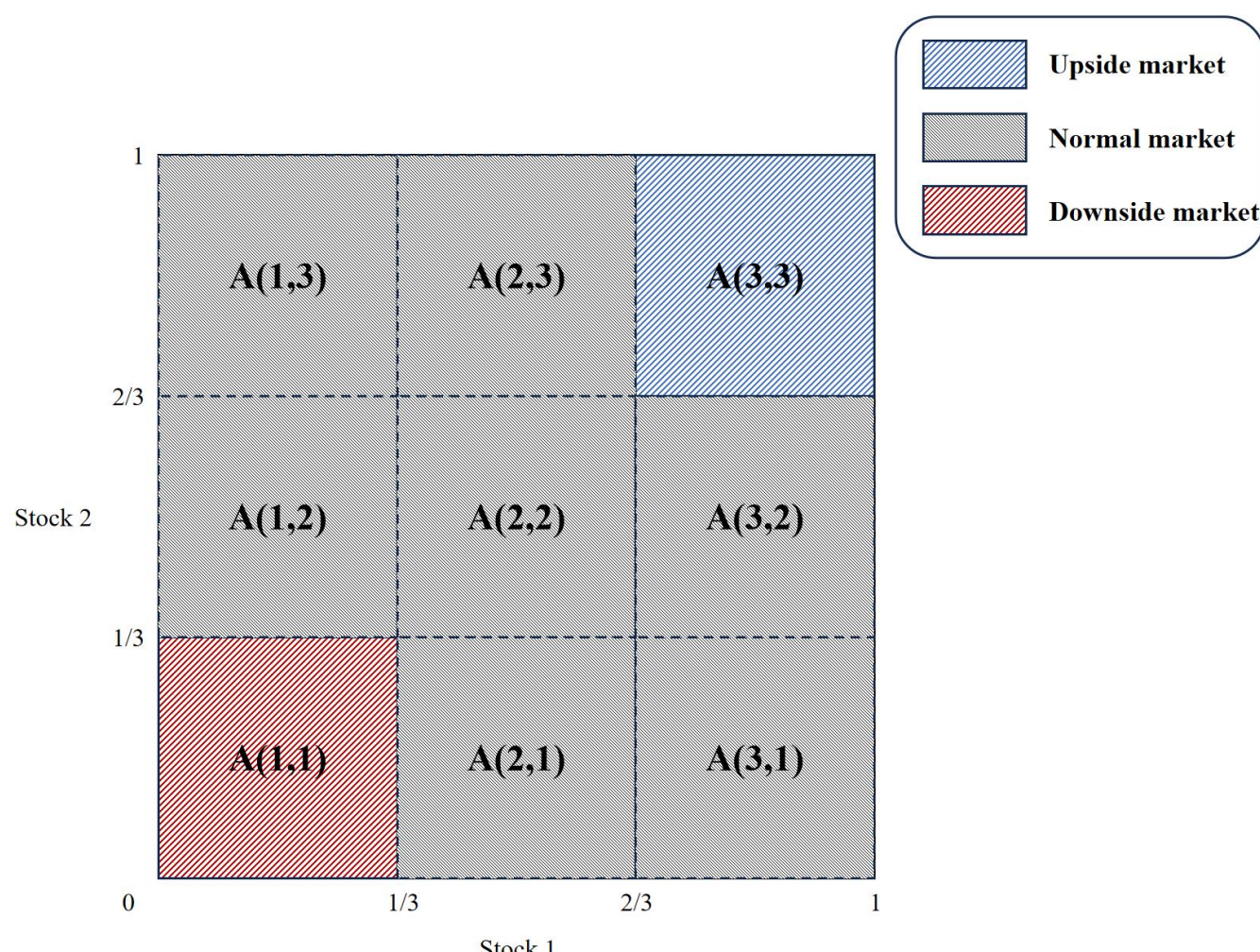
1 Patched Bivariate Fréchet Copula model

- Combines market segmentation and correlation structure decomposition
- Providing more useful structured information for risk management
- Using the mixed Copula function $C_{\alpha_{i,j}, \gamma_{i,j}}^F$ to approximate the original Copula function $C_{i,j}$

$$\min S_{i,j}(\alpha_{i,j}, \gamma_{i,j})$$

$$\text{s.t. } 0 \leq \alpha_{i,j}^*, \gamma_{i,j}^* \leq 1, \alpha_{i,j}^* + \gamma_{i,j}^* \leq 1$$

$$S_{i,j}(\alpha_{i,j}, \gamma_{i,j}) = \int_{\frac{i}{m}}^{\frac{i+1}{m}} \int_{\frac{j}{m}}^{\frac{j+1}{m}} \{C^{i,j}(F_{i,j}(u), G_{i,j}(v)) - C^F_{\alpha_{i,j}, \gamma_{i,j}}(F_{i,j}(u), G_{i,j}(v))\}^2 du dv$$



2 Parallel Optimization of Data Preprocessing for Multiple Correlation Structure Decompositions

- LOOP: two 'for' --> combined one 'for'
- Workstation: expanded to 210 threads
- 30 threads Case: 25.88x faster than the original program (32,683 (s)).

Threads	30	60	90	120	150	180	210
Time(s)	1263	848	632	476	335	212	105
Relative Speedup	1	1.49	2.00	2.65	3.77	5.96	12.03

3 The Deep Learning Algorithms for This Problem

- Classical: RNN, LSTM, GRU
- Ensemble: AWEA, EDAA, RFEA
 - AWEA: Averaging the prediction results of RNN, LSTM, and GRU.
 - EDAA: Select the better result algorithm LSTM and GRU. The LSTM-GRU model is best suited.
 - RFEA: Random Forest Ensemble Algorithm.

5 Further Research

- The correlation structure between multiple asset data of various countries is predicted using various deep learning models to study simulation effects using more efficient parallel methods.
- Based on the existing model, exogenous variables such as a country's economic policy, foreign trade, are added to further improve the model's prediction effect, interpretability, and universality.

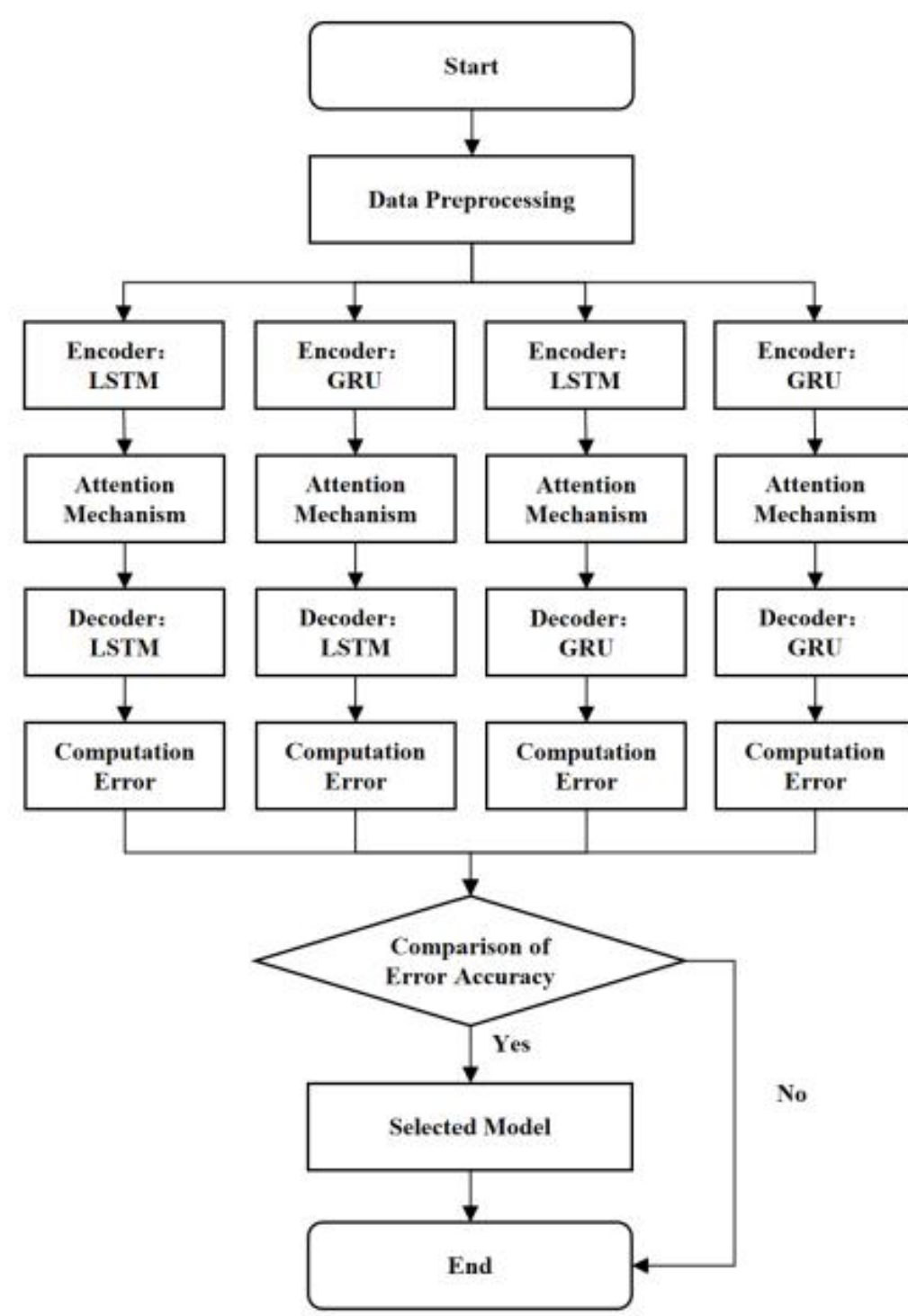


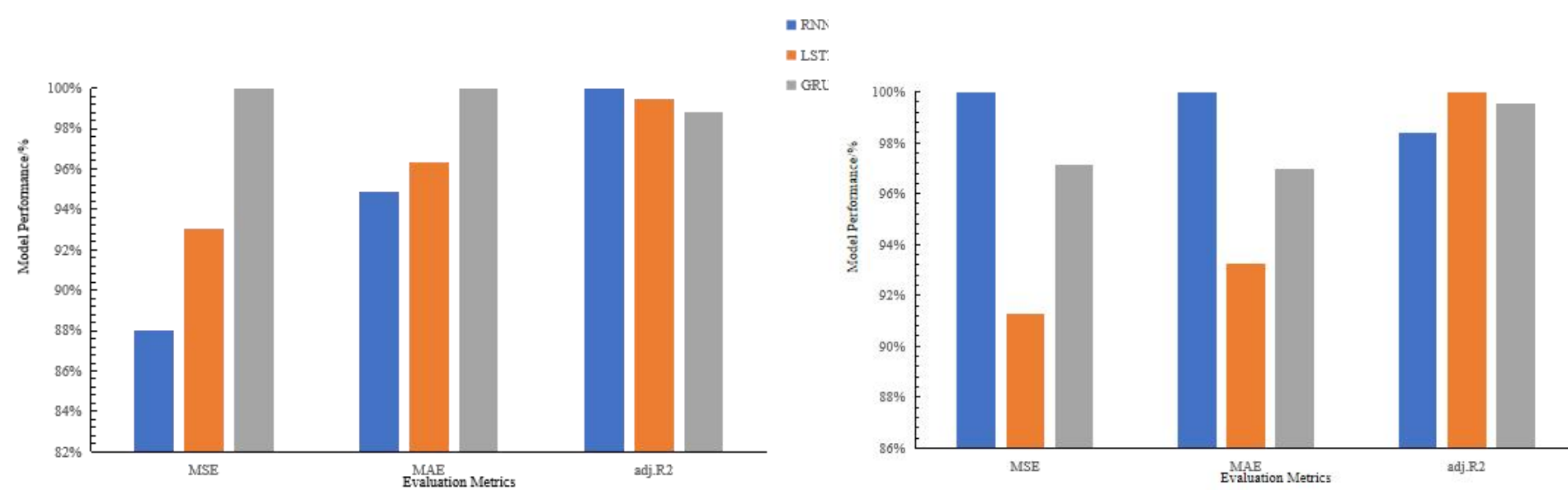
Fig. The Encoder-Decoder Model

4 Experimental Results

- Results of RNN/LSTM/GRU Algorithm

TABLE III. PERFORMANCE OF RNN/LSTM/GRU MODELS ON CORRELATION STRUCTURE PREDICTION PROBLEM

Model	RNN	LSTM	GRU
Global Alpha			
Time(s)	23.729	17.657	23.546
MSE	1.343E-04	1.420E-04	1.526E-04
MAE	8.951E-03	9.091E-03	9.437E-03
\bar{R}^2	0.925	0.920	0.914
Global Gamma			
Time(s)	6.540	9.989	7.750
MSE	9.724E-05	8.875E-05	9.446E-05
MAE	7.785E-03	7.259E-03	7.550E-03
\bar{R}^2	0.848	0.862	0.853



- Results of Ensemble Algorithms

TABLE IV. PERFORMANCE OF AWEA/EDAA/RFEA MODELS ON CORRELATION STRUCTURE PREDICTION PROBLEM

Model	AWEA	EDAA	RFEA
Global Alpha			
Time(s)	4.983E-05	32.114	0.276
MSE	1.871E-04	1.887E-04	1.947E-05
MAE	0.0105	0.0111	0.0034
\bar{R}^2	0.9498	0.9494	0.9948
Global Gamma			
Time(s)	4.387E-05	34.930	0.270
MSE	2.416E-05	2.096E-05	3.129E-06
MAE	0.0035	0.0032	0.0012
\bar{R}^2	0.8978	0.9113	0.9868

